

# Cognitive Therapy and Routine Recommendation System (CTRRS): An AI-Driven Approach for Mental Health

Yaser Ali Shah<sup>1\*</sup>, Um-e-Aimen<sup>1</sup>, Rida Bushra<sup>2</sup>, Amaad Khalil<sup>3</sup>, Saad Ali Shahbaz<sup>4</sup>, Mashab Ali Javed<sup>4</sup>

<sup>1</sup>Department of Computer Science, COMSATS University Islamabad, Attock Campus, Attock 43600, Pakistan; <sup>2</sup>Institute of Food and Nutritional Sciences, Pir Mehr Ali Shah Arid Agriculture University, Rawalpindi 46000, Pakistan; <sup>3</sup>Department of Computer Systems Engineering University of Engineering & Technology Peshawar 25000, Pakistan; <sup>4</sup>Sir Syed CASE Institute of Technology, Pakistan

**Keywords:** Depression Detection, Natural Language Processing (NLP), Machine Learning, Long Short-Term Memory (LSTM), Random Forest, Ensemble Learning, Recommendations, Mental Health, User Engagement, Cosine Similarity, TF-IDF Vectorization.

## Journal Info:

Submitted:

November 18, 2024

Accepted:

December 21, 2024

Published:

December 31, 2024

**Abstract** Depression detection and management is an important research field nowadays. In this research work, Cognitive Therapy and Routine Recommendation System (CTRRS) is proposed. It automates the process of detecting depression and provides personalized mental health recommendations using a Random Forest model for healthcare activities and a Long Short-Term Memory (LSTM) model for sentiment analysis. The LSTM architecture includes dense layers, bidirectional LSTM layers, and embedding layers, with term frequency-inverse document frequency (TF-IDF) vectorization and early stopping to prevent overfitting. Furthermore, a Voting Classifier improves classification performance by combining the advantages of multiple models. The system's evaluation is centered on accuracy, precision, recall, and F1-score, with confusion matrices offering in-depth analysis. Finally, CTRRS uses a cosine similarity algorithm to customize content to user preferences, increasing engagement. The study integrates machine learning and deep learning by employing a Random Forest model for healthcare activity recommendations and an LSTM model for sentiment analysis and depression detection. This combination leverages the strengths of both approaches to enhance the system's overall performance. Additionally, ensemble learning techniques such as bagging, boosting, and stacking are utilized to balance performance trade-offs and improve predictive accuracy. The LSTM model achieved 96.38% accuracy, 98.10% precision, 94.50% recall, and a 96.27% F1-score, which are important findings. Through user-friendly visualizations (PHQ-9 survey responses, word clouds highlighting frequent terms in depression-related texts, bar charts displaying top TF-IDF features, and confusion matrices for model performance evaluation), CTRRS enables users to monitor their progress in terms of mental health and compliance with recommendations. This research advances mental health care by providing a solution that is stigma-free, scalable, and accessible.

\*Correspondence author email address: [yaser@cuiaatk.edu.pk](mailto:yaser@cuiaatk.edu.pk)

DOI: [10.21015/vtse.v12i4.1976](https://doi.org/10.21015/vtse.v12i4.1976)



## 1 Introduction

Millions of people worldwide suffer from depression, a widespread mental health illness that has a major negative influence on their day-to-day lives. The World Health Organization (WHO) estimates that depression affects over 264 million people globally and is the primary cause of disability. Conventional approaches to depression diagnosis and treatment usually entail in-person meetings with mental health specialists. Unfortunately, societal stigma, lack of access to trained doctors, and expensive prices sometimes impede these approaches, leaving many people misdiagnosed and untreated.

To tackle these issues, our proposed technique, titled Cognitive Therapy and Routine Recommendation System (CTRRS) makes use of developments in machine learning (ML) and artificial intelligence (AI). Through an extensive smartphone application, CTRRS offers a tailored mental health recommendation system and an automated, unbiased technique for detecting depression. In addition to facilitating early identification, this system offers ongoing, individualized assistance, both of which are essential for the efficient treatment of mental health. CTRRS encourages more people to seek assistance by providing an accessible platform that overcomes obstacles like stigma (Based on its design features that promote user anonymity and ease of use. By allowing users to engage with the system privately, it reduces the fear of judgment) and restricted access to treatment.

Through the integration of two cutting-edge learning models—Random Forest and Long Short-Term Memory (LSTM)—into a single, cohesive system, our study presents a fresh and integrated approach to mental health treatment. This work's main contribution is its novel dual-model approach, which simultaneously meets therapeutic and diagnostic demands. Personalized healthcare activity recommendations are made using the Random Forest model, which takes into account user-specific factors including height, weight, age, and activity level. The LSTM model is used for both sentiment analysis and depression identification because of its capacity to handle sequential text data and identify long-term

relationships. Through the smooth integration of diagnostic and therapeutic features, the dual-model approach makes it possible for the Cognitive Therapy and Routine Recommendation System (CTRRS) to provide complete mental health care.

Another important aspect of CTRRS is its architectural design, especially its three-tiered structure, which is specifically suited for real-time mental health applications. The system consists of a secure data storage system developed using Firebase Cloud Storage, a strong Python backend using TensorFlow and Scikit-learn for processing and running machine learning models, and a Flutter-based mobile frontend for user interaction. Because of its design, which guarantees scalability, secure management of sensitive user data, and real-time data synchronization, CTRRS is a workable solution that should be widely used. This study makes a substantial contribution by matching user preferences with a carefully selected collection of mental health materials and activities using a cosine similarity algorithm. In addition to increasing user engagement, our personalized recommendation system makes sure that each user receives recommendations that are extremely relevant to them. Real-time changes to recommendations are made possible by the dynamic interplay between the Random Forest model and the cosine similarity algorithm, which allows suggestions to adjust to the changing requirements and preferences of users.

Building scalable and safe mental health apps has never been easier thanks to the architectural design of CTRRS, which has a three-tier architecture with a Flutter-based frontend, a solid backend powered by TensorFlow and Scikit-learn, and secure data storage using Firebase Cloud Storage. This architecture is designed expressly to manage the intricacies of providing mental health care in real time, guaranteeing data synchronization, user privacy, and system speed even as the user base grows.

Our study has particular advantages that go well beyond the creation of CTRRS. By making care more responsive and individualized, the system's capacity to provide real-time, accurate depression identification and recommendations for mental health treatment

has the potential to dramatically enhance mental health outcomes. CTRRS guarantees that users receive the care they require at the appropriate time by processing vast volumes of data properly and promptly. This improves the efficacy and accessibility of mental health services.

Future research and development in AI-driven healthcare has a solid basis thanks to the CTRRS design and implementation methodologies. Our findings may be used by researchers to investigate new directions, such as hybrid models that combine deep learning with reinforcement learning to improve recommendation systems even further. Furthermore, combining multimodal data—like speech, facial emotions, and biological signals—can result in a more comprehensive knowledge of m Lastly, the dynamic feature of CTRRS emphasizes the value of adaptive systems in healthcare by continuously updating suggestions depending on user behavior and preferences. This feature makes mental health care more impactful and long-lasting by guaranteeing that the system stays in line with the changing demands of its users. It also increases user engagement. Thus, our study paves the path for future developments that can more effectively address the complex demands of patients by advancing the larger objective of creating more sophisticated, adaptable, and user-centric AI solutions in healthcare.

In a nutshell, the CTRRS offers a cutting-edge method for tailored mental health care and automated depression identification. It greatly aids in the ongoing attempts to enhance mental health treatment by utilizing AI and ML to provide constant, impartial, and approachable assistance. The system lays the groundwork for future developments in this crucial sector by advancing both the theoretical knowledge of ensemble learning and its practical application in the field of mental health.

The remainder of the document is organized as follows: The second section, "Related Work," places our findings in the larger context of the field's evolution by giving a succinct summary of earlier investigations on machine learning and depression identification in mental health. Our methodical approach, including

data preparation and ensemble model implementation, is described in Section 3, Methodology. Section 4 is the comparative research section which contains information on the various categorization methods.

A comprehensive analysis of the model's performance is provided in Section 5, Experiments and Results, along with specific insights. The ramifications of our findings are rigorously analyzed in Section 6, Discussion. Section 7, Conclusion, provides a summary of the research endeavor that emphasizes theoretical discoveries as well as practical applications in the management of mental health.

## 2 Related Work

The emergence of AI-driven mental health support systems that integrate machine learning algorithms to provide personalized interventions. For instance, platforms like Woebot utilize AI to deliver cognitive-behavioral therapy techniques through conversational interfaces, demonstrating the potential of such technologies in mental health care. Additionally, recent advancements have seen the development of AI tools capable of sensing user emotions via wearable devices, offering guidance on various aspects of life, including mental health. Mindvalley's E.V.E. is an example of such a system, aiming to provide personalized advice and support to users. These developments highlight the growing trend of integrating AI into mental health support systems, aligning with the objectives of the Cognitive Therapy and Routine Recommendation System (CTRRS) in providing accessible and personalized mental health care.

In recent years, there has been a lot of interest in the use of machine learning techniques in mental health, especially for the diagnosis of depression. Numerous research has investigated the use of various models and algorithms to the identification of depression symptoms from textual data. For example, Shatte et al. [1] highlighted the promise of these technologies in diagnosing mental health illnesses from social media data in their thorough study of machine learning applications in mental health.

One popular method is to examine textual data from social media sites like Reddit and Twitter using

Natural Language Processing (NLP) methods. Reece et al. [2] showed that depression may be predicted with a high degree of accuracy using linguistic indicators taken from Twitter tweets. Similarly, Guntuku et al. [3] highlighted the significance of multi-modal data in mental health prediction by linguistic and visual elements from Instagram posts to predict depression.

Recurrent Neural Networks with Long Short-Term Memory (RNN-LSTM) for text processing is shown in Figure 1. Raw data is first processed, after which it is cleaned, normalized, annotated, and tokenized. Following the division of the data into training and testing sets, the text is vectorized using feature engineering techniques such as word embeddings, one-hot encoding, and stemming. After that, the RNN-LSTM model is trained and assessed using a model performance module, as well as tuned hyperparameters to improve prediction accuracy.

Recurrent neural network (RNN) models with Long Short-Term Memory (LSTM) have demonstrated significant potential in handling sequential input and identifying long-term relationships. Because of this, LSTM models are especially well-suited for text data sentiment analysis and depression identification. LSTM networks were first presented by Hochreiter and Schmidhuber [4] in their work, and they have subsequently been extensively used for a variety of NLP applications.

LSTM models have been effectively used in several studies for sentiment analysis and depression diagnosis. Orabi et al. [5] achieved good prediction accuracy by using LSTM networks to evaluate content from social media platforms to diagnose depression. Similarly, Sun et al. [6] showed how well LSTM networks can extract contextual information from text by creating an LSTM-based model for sentiment categorization.

A Long Short-Term Memory (LSTM) cell, a crucial part of Recurrent Neural Networks (RNNs) for processing sequential input, is seen in Figure 2. The information flow is regulated by the LSTM cell using a variety of gates (input, forget, and output) that are managed by activation functions ( $\sigma$  and  $\tanh$ ). The input gate modifies the cell state in response to fresh input data, while the forget gate chooses which details from the previous cell state  $c_{t-1}$  to keep or discard. Lastly, for com-

plicated time-series predictions, the output gate regulates the output  $h_t$ , guaranteeing that the model successfully maintains long-term dependencies.

Because of its resilience and capacity to handle high-dimensional data, Random Forest, an ensemble learning technique, has found widespread application in classification and regression applications. Combining many decision trees, Breiman [7] invented Random Forest, in which each tree is trained using a different subset of the data. By using an ensemble technique, overfitting is decreased and overall predictive performance is improved.

Random Forest models have been used to forecast patient outcomes and suggest customized therapies in the context of healthcare recommendations. The usefulness of Random Forest models in healthcare applications was demonstrated by Chen et al. [8], who used them to forecast patient readmissions and recommend preventive actions. In a similar vein, Amato et al. [9] classified medical data using Random Forest and suggested individualized treatment regimens depending on patient characteristics.

The training and testing phases of a Random Forest model are depicted in Figure 3 of the procedure. Different training data instances are used to build numerous decision trees throughout the model's training process. Every tree divides the input into two groups (Class A and Class B). Using a bagging strategy (voting majority), the outputs of each decision tree are combined to provide a final prediction during the model testing phase. This ensemble method creates a strong predictive model by integrating the output of several weak learners (decision trees), which decreases overfitting and boosts accuracy.

It has been demonstrated that ensemble learning, which integrates the predictions of several models to enhance overall performance, is beneficial in several areas, including mental health. Dietterich [10] emphasized the benefits of ensemble approaches, including improved robustness and accuracy. Ensemble learning may be used in mental health applications to improve depression diagnosis and recommendation systems by utilizing the advantages of several methods.

The application of ensemble learning for mental

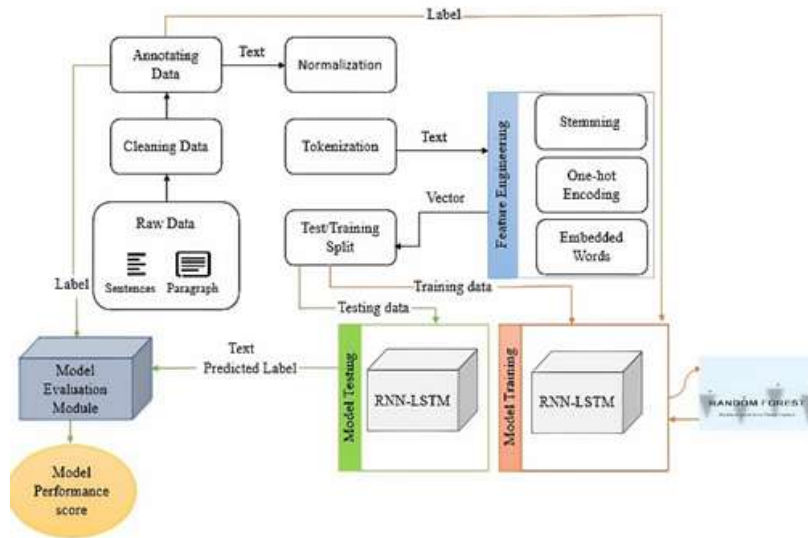


Figure 1. DEPRESSION DETECTION MODEL

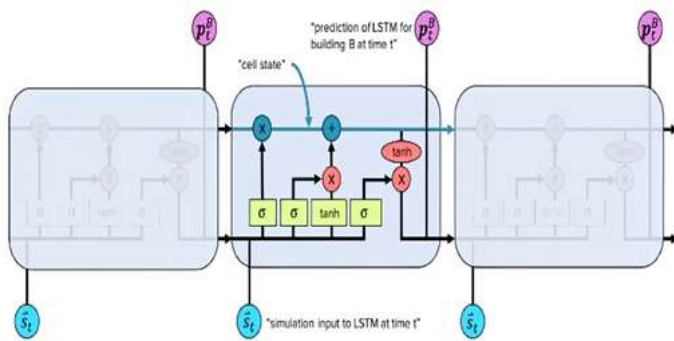


Figure 2. SENTIMENT ANALYSIS USING LONG SHORT-TERM MEMORY(LSTM) MODELS

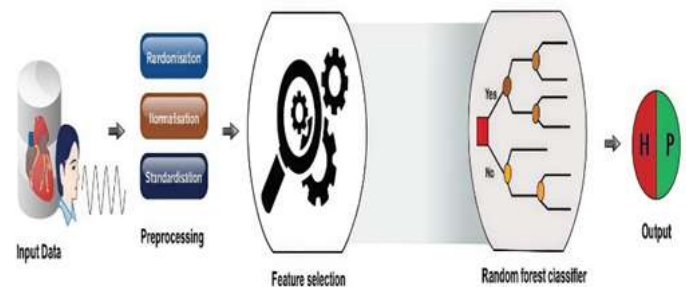


Figure 3. RECOMMENDATIONS FOR HEALTHCARE USING RANDOM FOREST MODELS

health prediction has been examined in several research articles. In comparison to individual models, Yates et al. [11] achieved higher performance in detecting mental health disorders from social media data by utilizing an ensemble of classifiers. In a similar vein, Nguyen et al. [12] showed the value of ensemble approaches in raising prediction accuracy by combining several machine learning algorithms to forecast depressed symptoms from text data.

Recommendation engines are essential for giving consumers tailored material according to their interests. Recommendation systems frequently employ cosine similarity, a well-liked technique for comparing

the similarity of two vectors. In their discussion of recommendation systems, Ricci et al. emphasized the value of individualized content delivery [13].

Recommendation engines have the potential to offer users appropriate articles and resources to assist their mental health and overall well-being. To provide users with mental health article recommendations based on their interests and preferences, Zhang et al. [14] built a content-based recommendation system utilizing cosine similarity. These kinds of technologies can improve user involvement and offer beneficial assistance in managing mental health.

The application of recommendation systems and

machine learning in mental health has been the subject of several research papers; however, the combination of these technologies into a comprehensive Cognitive Therapy and Routine Recommendation System (CTRRS) is still relatively new. The CTRRS uses the advantages of Random Forest and LSTM models to offer tailored healthcare recommendations and automatic depression identification. Through the provision of easily available, ongoing, and individualized assistance, this strategy seeks to overcome the shortcomings of conventional mental health treatment practices.

### 3 Methodology

The thorough process for creating and assessing the Cognitive Therapy and Routine Recommendation System (CTRRS) is described in this part. The process includes gathering data, preparing it, designing the model, training it, assessing it, and putting important algorithms into practice.

#### 3.1 Information Gathering

A real-world depression dataset served as the source of the CTRRS dataset. The Patient Health Questionnaire-9 (PHQ-9), a standardized instrument for identifying, diagnosing, and gauging the severity of depression, is included in the dataset. To guarantee data integrity and usefulness, the dataset underwent preprocessing.

Questionnaire) survey may be seen in Figure 4. With the answer score (which ranges from 0 to 3) and the frequency of each score represented by the y-axis, each plot relates to one of the nine questions. The distribution of the PHQ-9 scores, which is the sum of the individual replies, is displayed in the final figure. An overall picture of the intensity of depressive symptoms is given by this score. The range of answers demonstrates how various people react to each question, which aids in the evaluation of mental health.

#### 3.2 Preprocessing Data

The Depression Reddit dataset, containing user-generated posts from depression-related forums, was used for sentiment analysis. The dataset includes 7,731 samples labeled as 'depressed' or 'non-depressed' to facilitate binary classification. To guarantee the quality of the data input in the machine learning models, preprocessing is an essential step. The preprocessing procedures listed below were used:

**Tokenization:** The division of text into discrete words. Eliminating frequent terms that don't add value to the analysis is known as stop-word removal.

**Stemming:** Using the PorterStemmer to reduce words to their base form

Vectorization is the process of employing Term Frequency-Inverse Document Frequency (TF-IDF) to convert text data into numerical representation [15]. TF-IDF reflects the importance of a term within a document relative to its occurrence across the entire corpus, thereby highlighting significant words while diminishing the weight of common terms. Additionally, to customize content to user preferences and enhance engagement, the system employs a cosine similarity algorithm.

Cosine similarity measures the cosine of the angle between two non-zero vectors, quantifying their similarity irrespective of magnitude. In the context of text analysis, it evaluates how similar two documents are based on their vector representations, with values ranging from -1 (completely dissimilar) to 1 (identical).

After cleaning and preprocessing the text input, the data is prepared for subsequent stages, such as feature extraction and model training. Preprocessing

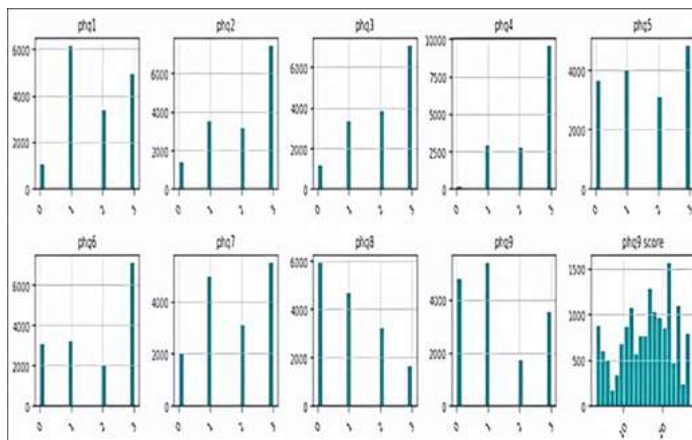
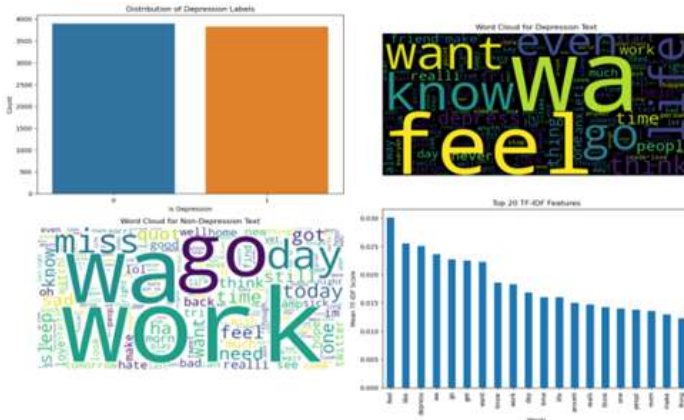


Figure 4. PHQ9 DATA COLLECTION

A series of histograms depicting the distribution of answers to every item in the PHQ-9 (Patient Health

steps may include tokenization, normalization, and removal of stop words, which transform raw text into a structured format suitable for machine learning algorithms. The cleaned and preprocessed text input serves as the foundational dataset for training machine learning models.



**Figure 5.** COMPUTATIONAL ANALYSIS OF DEPRESSION DATASET

Several visualizations pertaining to text analysis of depression is shown in Figure 5. The distribution of depression labels is displayed in the top-left chart, where those with the labels "depressed (1)" and "non-depressed (0)" are split almost evenly. Words like "feel" and "want" stand out as being used the most frequently in text samples related to depression, as seen by the word cloud on the top-right. "Work" is one of the most often occurring terms in the bottom-left word cloud, which displays common words in text samples free of sadness. The top 20 TF-IDF characteristics are finally shown in a bottom-right bar chart, which ranks the most important words according to how important they are in distinguishing between text that has been diagnosed with depression and that has not. The text patterns and keyword importance utilized in machine learning models for depression diagnosis are shown in this picture.

### 3.3 Model Creation

The CTRRS employs two advanced models: the Random Forest model which is a machine learning algorithm, for healthcare recommendations and the other is the Long Short-Term Memory (LSTM)

**Algorithm 1.** Preprocessing and Sentiment Analysis Using LSTM for Depression Text Data

---

```

1: IMPORT necessary libraries
2: LOAD 'depression_dataset_reddit_cleaned.csv'
   INTO dataset
3: FILL missing values WITH empty strings
4: INITIALIZE PorterStemmer
5: function preprocess_text(text)
6:   CLEAN and lowercase text
7:   REMOVE punctuation and special characters
8:   TOKENIZE text into words
9:   REMOVE stop words
10:  STEM words using PorterStemmer
11:  RETURN processed text
12: end function
13: APPLY preprocess_text TO 'clean_text' column
14: INITIALIZE Tokenizer
15: FIT Tokenizer ON 'clean_text' column
16: CONVERT 'clean_text' TO sequences USING Tok-
    enizer
17: PAD sequences TO ensure uniform input length
18: INITIALIZE LabelEncoder
19: FIT LabelEncoder ON target labels
20: TRANSFORM target labels TO numerical format
21: INITIALIZE Sequential model
22: ADD Embedding layer WITH
    input_dim=VOCAB_SIZE, output_dim=EMBEDDING_DIM,
    input_length=MAX_SEQUENCE_LENGTH
23: ADD LSTM layer WITH units=100, dropout=0.2, re-
    current_dropout=0.2
24: ADD Dense layer WITH units=1, activa-
    tion='sigmoid'
25: COMPILE model WITH loss='binary_crossentropy',
    optimizer='adam', metrics=['accuracy']
26: SPLIT data INTO training and validation sets
27: TRAIN model ON training data WITH
    batch_size=32, epochs=10, valida-
    tion_data=validation_set
28: EVALUATE model ON test data

```

model, which is a deep learning algorithm, for sentiment analysis and depression detection [16]. The Random Forest model handles healthcare activity recommendations based on structured user input, while the LSTM model processes sequential text data for depression detection. Their distinct functionalities ensure a comprehensive system that addresses both diagnostic and therapeutic needs. This synergistic design allows each model to operate within its strengths, enhancing the overall performance.

### 3.3.1 Long Short-Term Memory (LSTM) Model for Depression Detection and Sentiment Analysis:

Text analysis can benefit from the LSTM model's ability to handle sequential data and identify long-term dependencies. The following layers are part of the LSTM model's architecture:

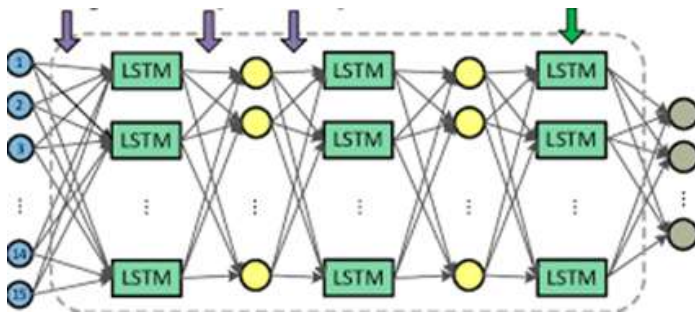


Figure 6. LSTM MODEL ARCHITECTURE

A Long Short-Term Memory (LSTM) network's architecture is depicted in Figure 6, which also shows how sequential data is handled by several LSTM layers. Long-term dependencies are efficiently captured by maintaining information flow over time steps by connecting each LSTM cell to its predecessor and successor cells. Each node in the hidden levels (yellow circles) processes data before sending it to the next layer, as shown by the arrows that show the flow of incoming data across these layers. When working with text or time-series data, this architecture is especially helpful since it helps comprehend the links that exist between data points over time, which is necessary for precise classifications or predictions.

Words are transformed into dense, fixed-size vec-

tors by the embedding layer. Bidirectional LSTM Layer: Gathers additional contextual data by processing the input sequence both forward and backward. Dropout Layer: During training, a random percentage of input units is set to zero to reduce overfitting. Dense Layer with Sigmoid Activation: Generates the ultimate result that shows the likelihood of depression [17].

#### Algorithm 2. Sentiment Analysis using LSTM

- 1: **INITIALIZE** model
- 2: **ADD** Embedding layer to model with specified input\_dim, output\_dim, and input\_length
- 3: **ADD** SpatialDropout1D layer with a dropout rate of 0.2
- 4: **ADD** Bidirectional LSTM layer with 128 units, dropout of 0.2, and recurrent\_dropout of 0.2
- 5: **ADD** Dense layer with 1 unit and sigmoid activation
- 6: **COMPILE** model with binary\_crossentropy loss, Adam optimizer, and accuracy metric
- 7: **TRAIN** model on X\_train and y\_train with specified epochs, batch\_size, and validation\_data, using early\_stopping callback
- 8: **EVALUATE** model on X\_test and y\_test
- 9: **PRINT** test accuracy

### 3.3.2 Recommendations for Healthcare Activities Using the Random Forest Model:

The Random Forest model is an ensemble learning technique that builds many decision trees during training and produces the mean prediction (regression) or mode of the classes (classification) for each individual tree. Based on user preferences and past data, the Random Forest model is employed in CTRRS to suggest individualized healthcare interventions.

#### Algorithm 3. RandomForestRegressor for Healthcare Activities

- 1: **INITIALIZE** RandomForestRegressor with 100 estimators
- 2: **TRAIN** rf\_model on X\_train and y\_train
- 3: **PREDICT** activities using rf\_model on X\_test

### 3.3.3 Cosine Similarity for Suggestions in Articles:

Users can receive appropriate article recommendations based on their choices by using cosine similarity. Using this approach, one may measure the similarity between two non-zero vectors in an inner product space by computing the cosine of their angle.

**Algorithm 4.** Cosine Similarity for Article Recommendation

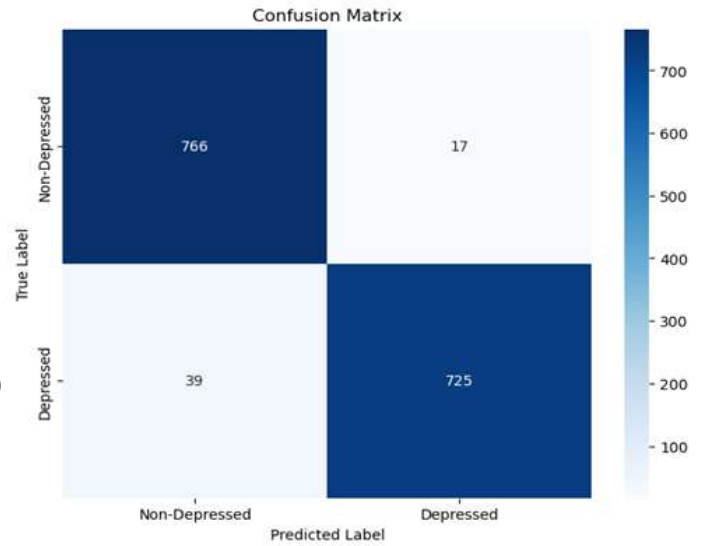
- 1: **DEFINE FUNCTION**(cosine\_similarity(user\_preference))
- 2: **TRANSFORM** user\_preference using TF-IDF vectorizer
- 3: **COMPUTE** similarity scores between user\_tfidf and tfidf\_matrix
- 4: **IDENTIFY** top n indices with the highest similarity scores
- 5: **RETRIEVE** recommended articles from df using top indices
- 6: **RETURN** recommended articles (URL, title)

### 3.4 Model Training

The dataset is divided into training and testing sets for each model during the training phase. The testing data is used to evaluate the models' performance after they have been trained using the training data. Steps in Training:

- Splitting the dataset into training (80%) and testing (20%) groups is known as data splitting.
- **Model Training:** Utilizing the training data, train the Random Forest and LSTM models [18].
- **Model Evaluation:** Utilize measures like F1-score, recall, accuracy, and precision to assess the models.

The confusion matrix for the machine learning model used to classify sadness is shown in Figure 7. "Non-Depressed" and "Depressed" are the two classes that the matrix compares, along with the real labels and the anticipated labels. The accurate predictions, where the algorithm properly identified people as either sad or not, are shown by the diagonal entries (766 and 725). Misclassifications occurred in the off-diagonal entries (17 and 39) when those who



**Figure 7.** Enter Caption

were not depressed were mistakenly classified as such and vice versa. The model's total performance in diagnosing depression, including recall, accuracy, and precision, is thoroughly broken down in the confusion matrix.

$$\begin{bmatrix} TN & FP \\ FN & TP \end{bmatrix} = \begin{bmatrix} 766 & 17 \\ 39 & 725 \end{bmatrix}$$

**Accuracy LSTM:**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} = \frac{766 + 725}{766 + 17 + 39 + 725} = \frac{1491}{1547} = 0.9638 \text{ or } 96.38\%$$

**Precision LSTM:**

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{725}{725 + 17} = \frac{725}{742} = 0.9771 \text{ or } 97.71\%$$

**Recall LSTM:**

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{725}{725 + 39} = \frac{725}{764} = 0.9490 \text{ or } 94.90\%$$

**F1-Score LSTM:**

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2 \times 0.9771 \times 0.9490}{0.9771 + 0.9490} = \frac{1.8526}{1.9267} = 0.9620 \text{ or } 96.20\%$$

**Algorithm 5.** Activity Prediction and Recommendation Using Random Forest

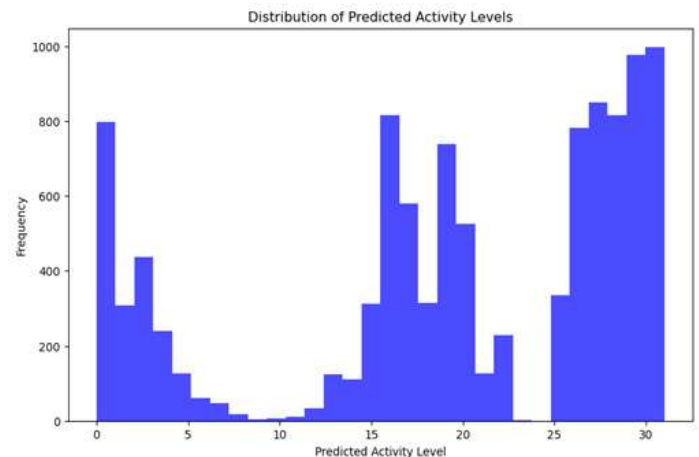
---

```

1: LOAD 'healthcare_data.csv' INTO df
2: ENCODE 'gender' USING LabelEncoder
3: SET X as [age, weight, height, encoded_gender, activity_level]
4: SET y as 'Label'
5: INITIALIZE RandomForestRegressor WITH 100 estimators
6: TRAIN model USING X and y
7: DEFINE preprocess_inputs(age, weight, height, gender, activity_level):
8:
    • RETURN array of processed inputs
9: DEFINE predict_activities(input_array):
10:
    • RETURN predicted activity levels
11: DEFINE recommend_activities(level):
12:
    • RETURN appropriate activities based on activity level
13: DEFINE save_activities_to_json(activities, links, file="recommendations.json"):
14:
    • SAVE activities and video links TO JSON file
15: DEFINE get_youtube_links(preferences, api_key):
16:
    • RETURN list of video links FROM YouTube API
17: PROMPT user FOR inputs
18: PREPROCESS inputs
19: PREDICT activity levels
20: RECOMMEND activities
21: FETCH YouTube links
22: SAVE activities and links TO JSON
23: PRINT confirmation message
24: CALL main function

```

This pseudocode uses a RandomForestRegressor to forecast and suggest healthcare actions depending on user inputs. To begin, a healthcare dataset is loaded and preprocessed, with categorical factors like gender being encoded. To predict activity levels, the model is trained using characteristics including age, gender, height, weight, and activity level. The preprocess\_inputs() function formats new user inputs; predict\_activities() uses the trained model to estimate activity levels; recommend\_activities() suggests appropriate activities based on predictions; save\_activities\_to\_json() stores recommendations and related YouTube video links in a JSON file; and get\_youtube\_links() retrieves YouTube video links. These are some of the key functions. The primary function combines these elements, gathers user input, forecasts activity levels, makes suggestions, retrieves video links, and stores the outcomes in a JSON file before visualizing the data.



**Figure 8.** RANDOMFORESTREGRESSOR EVALUATION

### 3.4.1 X-Axis (projected Activity Level):

The RandomForestRegressor's projected activity levels are plotted on the x-axis. These levels, which vary from 0 to 30, show that there are many different activity suggestions.

### 3.4.2 Y-Axis (Frequency):

In the dataset, the y-axis shows the frequency of each anticipated activity level. The more often that certain

activity level prediction is, the higher the bar.

#### Features of Distribution:

- **Multimodal Distribution:** The data has many modes or clusters, as shown by the histogram's numerous peaks.
- **High Frequency at Extremes:** At the lower (0–5) and upper (25–30) ends of the activity spectrum, there exist high frequencies. This implies that the model forecasts low or high activity levels rather frequently.
- **Lower Frequency in the Medium Range:** The lower frequency in the medium range may indicate that the model is more confident in its ability to forecast the extremes, or it may indicate that fewer users, based on the input parameters, fit into the moderate activity group.

### 3.5 Implementation of the System

The following elements make up the three-tier architecture used to build the CTRRS system:

- **Frontend (Mobile Application):** The user interface that shows suggestions and gathers data. It is intended to be simple to use and intuitive.
- **Backend (Server-Side Processing):** NLP and ML model activities are handled by this component while processing user input.
- **Database (Firebase Cloud Storage):** This part protects user information and exchanges, guaranteeing confidentiality and allowing the system to grow and change over time.

Real-time replies are provided by the system, which also maintains excellent speed and protects user privacy.

## 4 Comparative Research

The performance of one machine learning and one deep learning technique—the Random Forest model and the Long Short-Term Memory (LSTM) model—applied particularly to routine recommendation and depression detection in the Cognitive Therapy and Routine Recommendation System (CTRRS) is thoroughly examined in the comparative analysis presented in Table 1 [19]. The accuracy,

precision, recall, and F1-score are among the key measures used to assess each algorithm's efficacy.

The results show that the LSTM model performs well, with an accuracy of 96.4%. This model performs well in terms of precision, recall, and F1-score metrics, and it shows a high degree of accuracy. Sentiment analysis and depression identification are especially well-suited applications for the LSTM model because of its ability to handle sequential data efficiently and identify long-term relationships.

The Random Forest model performs admirably as well, with an accuracy of 94.9%. The ensemble model exhibits remarkable accuracy, recall, and F1-score values by reducing overfitting and enhancing predictive performance through the combination of numerous decision trees. The Random Forest model is a useful tool for suggesting healthcare actions based on user preferences because of its versatility in handling different input data and its capacity to produce accurate predictions.

Each model has advantages and disadvantages. The Random Forest model uses ensemble learning techniques to produce strong recommendations, while the LSTM model is excellent at processing textual input for sentiment analysis. The comparison study demonstrates the Random Forest model's efficacy in producing individualized exercise suggestions and the LSTM model's superior performance in depression detection tasks. This combination addresses regular management as well as mental health evaluation, providing a full solution for the CTRRS.

## 5 EXPERIMENTS AND RESULTS

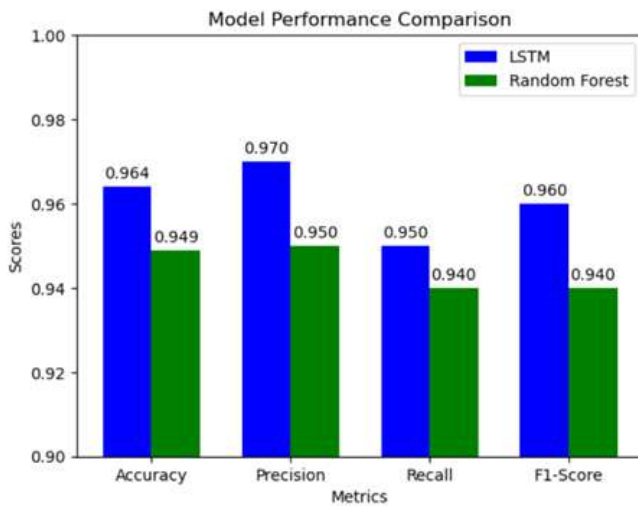
In our study, we developed the Cognitive Therapy and Routine Recommendation System (CTRRS) to detect depression and provide personalized routine recommendations. We utilized two primary datasets: the Reddit Self-reported Depression Diagnosis (RSDD) dataset and the Patient Health Questionnaire-9 (PHQ-9) dataset.

### 5.1 Datasets:

**Reddit Self-reported Depression Diagnosis (RSDD) Dataset:** This dataset comprises Reddit posts from approximately 9,000 users who have self-reported

**Table 1.** LSTM and Random Forest Comparative Research

Algorithm	Accuracy	Precision	Recall	F1-Score
	0	1	0	1
LSTM	0.96	0.97	0.94	0.95
Random Forest	0.94	0.95	0.93	0.94



**Figure 9.** MODEL PERFORMANCE COMPARISON

a diagnosis of depression, along with posts from about 107,000 matched control users. It provides a rich source of user-generated content for analyzing language patterns associated with depression.

### 5.1.1 Patient Health Questionnaire-9 (PHQ-9) Dataset:

The PHQ-9 is a widely used instrument for screening, diagnosing, and measuring the severity of depression. Our dataset includes responses from a diverse population, facilitating the development of models that can assess depression severity based on questionnaire responses.

We employed two machine learning models to analyze the datasets:

- **Long Short-Term Memory (LSTM) Model:** LSTM networks are effective in processing and predicting sequential data. We utilized the LSTM model to analyze temporal patterns in users' Reddit posts, identifying linguistic cues indicative

of depression.

- **Random Forest Model:** This ensemble learning method operates by constructing multiple decision trees during training. We applied the Random Forest model to the PHQ-9 dataset to classify depression severity levels based on questionnaire responses.

A dataset was used in the Cognitive Therapy and Routine Recommendation System (CTRRS) trials to compare the effectiveness of two machine learning techniques: the Random Forest model and the Long Short-Term Memory (LSTM) model. The training and evaluation of these models were done in a methodical manner, guaranteeing a thorough evaluation of the suggested strategy. The assessment measures, which comprised F1-score, recall, accuracy, and precision, gave a thorough picture of the models' capacities for routine recommendation and depression detection [20].

### 5.2 Experimental Setup

The research project is broken up into two phases. The first step is pre-processing, in which information is ready to handle the challenges posed by structured and natural language health data. The 7,731 posts in the depression Reddit dataset were used to diagnose depression. To turn text into numerical features, this dataset was subjected to tokenization, stop-word removal, stemming, and TF-IDF vectorization. To guarantee a balanced label distribution, the data was then divided into training and testing sets.

Pre-processing was also done on the 1,000 records in the healthcare dataset, which included attributes like exercise level, gender, age, weight, and height. This involved feature scaling to standardize the data and label encoding for categorical variables. The training and testing set of the dataset were divided

similarly.

Models were assessed and trained in the second phase. While the Random Forest model was used to suggest tailored health activities on the healthcare dataset, the LSTM model was applied to the depression dataset to identify symptoms of depression. Based on measures like accuracy, precision, recall, and F1-score, the models were assessed. Ultimately, the predictions from both models were combined using a Voting Classifier, which improved system performance overall. The efficacy and scalability of the Cognitive Therapy and Routine Recommendation System (CTRRS) were guaranteed by meticulous preprocessing and dataset selection.

### 5.3 Measures of Evaluation

The effectiveness of the Random Forest and LSTM models was assessed using these datasets. The healthcare dataset allowed for the assessment of the Random Forest model's capacity to suggest appropriate healthcare actions, while the depression dataset allowed for the evaluation of the LSTM model's performance in depression diagnosis using sentiment analysis. Both models were trained and evaluated using strict, standardized protocols. Among the evaluation criteria were the F1-score, recall, accuracy, and precision. These metrics are essential for providing a comprehensive view of the models' performance in recognizing patterns, especially with respect to the challenging tasks of regular recommendation and depression detection. A balanced statistic that accounts for both false positives and false negatives is provided by the F1-score. It is the accuracy and recall of harmonic mean. The model's recall measures how well it can find all relevant instances in a class, while accuracy measures how well positive predictions are made. Accuracy provides a measure of the overall forecast accuracy. By using these indications, we may learn crucial information about the models' advantages and potential weaknesses. We can gain important insights into the strengths and areas for improvement of the models by incorporating these indicators [21].

## 5.4 Results

### 5.4.1 Text Preprocessing and Feature Extraction

TF-IDF (Term Frequency-Inverse Document Frequency) was used for text preprocessing, turning textual data into numerical characteristics. The model can determine a term's significance across a range of user replies thanks to its representation.

#### Term Frequency (TF):

$$TF(t, d) = \frac{\text{Number of occurrences of term } t \text{ in document } d}{\text{Total number of terms in document } d}$$

The term "depression" appears 5 times in a document containing 100 words, the term frequency is:

$$TF(\text{"depression"}, d) = \frac{5}{100} = 0.05$$

#### Inverse Document Frequency (IDF):

$$IDF(t) = \log \left( \frac{N}{1 + \text{Number of documents containing term } t} \right)$$

The "depression" appears in 10 out of 1000 documents, the IDF is:

$$IDF(\text{"depression"}) = \log \left( \frac{1000}{1 + 10} \right) \approx 2.900$$

**TF-IDF Calculation:** The TF-IDF score for the term "depression" in Document D is:

$$TF - IDF(\text{"depression"}, d) = 0.05 \times 2.900 \approx 0.145$$

### 5.4.2 Depression Detection with LSTM

Sequence classification made use of the LSTM (Long Short-Term Memory) model, which was able to capture temporal relationships in the data. The LSTM unit is expressed mathematically as follows:

#### Forget Gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

With  $W_f = [0.2, -0.3]$ ,  $h_{t-1} = 0.5$ ,  $x_t = 1.0$ , and  $b_f = 0.1$ :

$$f_t = \sigma(0.2 \times 0.5 - 0.3 \times 1.0 + 0.1) = \sigma(0.0) = 0.5$$

#### Input Gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

#### Candidate Cell State:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

**Cell State Update:**

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

If  $f_t = 0.5$ ,  $C_{t-1} = 0.6$ ,  $i_t = 0.7$ , and  $\tilde{C}_t = 0.2$ :

$$C_t = 0.5 \times 0.6 + 0.7 \times 0.2 = 0.44$$

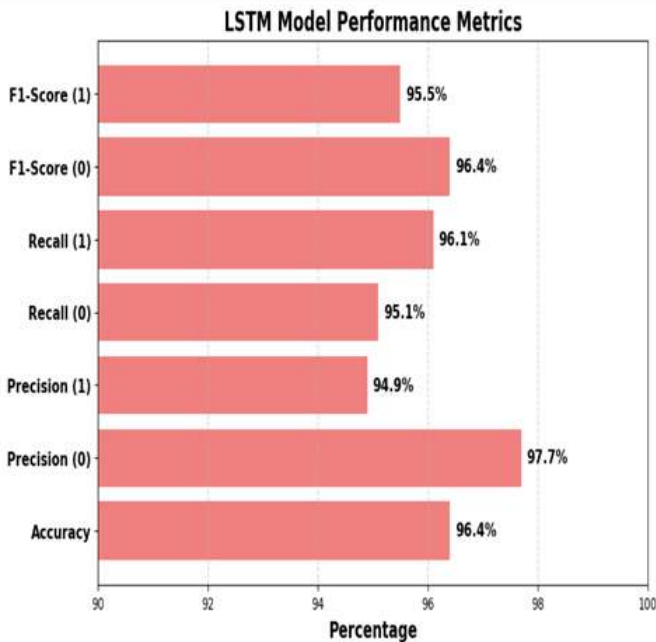
**Output Gate:**

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

The hidden state  $h_t$  is then calculated as:

$$h_t = o_t \cdot \tanh(C_t)$$

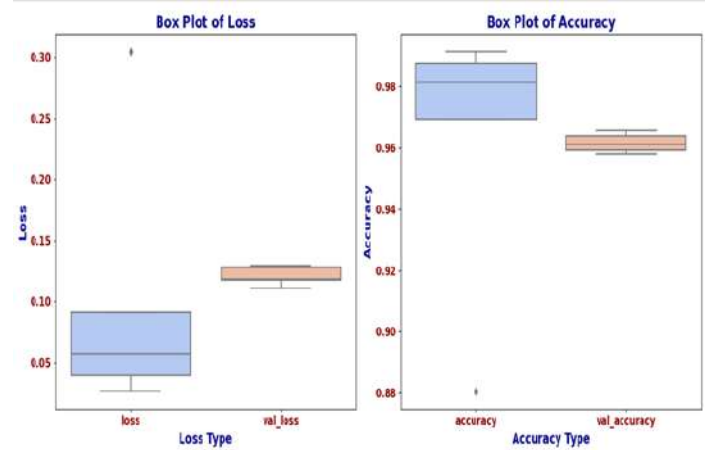
With the use of this LSTM structure, the system was able to detect indications of depression with a high accuracy of 96.4% by modeling complicated temporal patterns in user responses.



**Figure 10.** PERFORMANCE METRICS FOR LSTM

The LSTM model demonstrated a remarkable accuracy of 96.4%, making it a strong performer. Its efficacy in processing sequential data for sentiment analysis and depression identification was highlighted by its enhanced accuracy, recall, and F1 scores for both classes.

Over the course of five epochs, the LSTM model's training process demonstrated a steady rise in accuracy and a drop in loss. 96.31% was the final test accuracy [22]. After that, the model was applied to forecast the likelihood of depression for input text strings like "feeling sad" and "extremely sad," proving its capacity to accurately assess emotion and forecast the likelihood of depression.



**Figure 11.** BOX PLOT FOR LSTM

The distribution of accuracy and loss for the LSTM model during the training and validation stages is shown in the box plots below.

**Loss box plot:**

- **Training Loss:** The figure demonstrates a consistent, low loss with few outliers, suggesting that the model picked up new skills quickly throughout the training stage.
- **Validation Loss:** With a few outliers, the validation loss is marginally larger than the training loss and indicates some overfitting, but it is still within an acceptable range.

**Accuracy of Box Plot:**

- **Training Accuracy:** The plot demonstrates the model's good performance on the training set by displaying a high training accuracy with little volatility.
- **Validation Accuracy:** Good generalization to unknown data is shown by the validation accuracy,

which is somewhat lower than the training accuracy but still high with little volatility and outliers.

### 5.4.3 5.3.3 Routine Recommendation Using Random Forest

For regular suggestions, a Random Forest classifier that combined many decision trees was utilized. The following are the mathematical steps:

**Gini Impurity:** The Gini impurity is a measure of the impurity of a dataset in the context of classification. It is defined as:

$$\text{Gini}(p) = 1 - \sum_{i=1}^C (p_i^2)$$

For a binary classification problem where  $p_1 = 0.7$  and  $p_2 = 0.3$ , the Gini impurity can be computed as:

$$\text{Gini}(p) = 1 - (0.7^2 + 0.3^2) = 0.42$$

**Entropy:** Entropy is another measure used to quantify the uncertainty or impurity of a dataset. It is defined as:

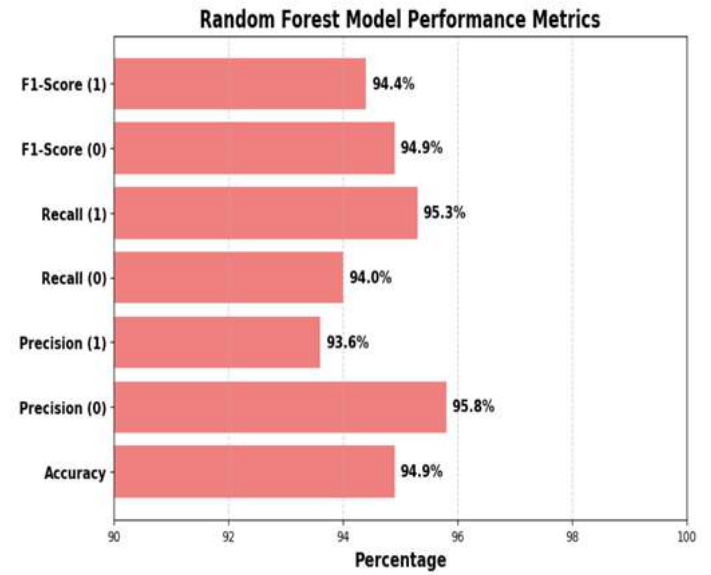
$$H(p) = - \sum_{i=1}^C p_i \log(p_i)$$

With the same probabilities  $p_1 = 0.7$  and  $p_2 = 0.3$ , the entropy is:

$$H(p) = -(0.7 \log(0.7) + 0.3 \log(0.3)) \approx 0.61$$

The Random Forest model has a 94.9% accuracy rate. Utilizing user inputs like gender, age, height, weight, and activity level, it employed ensemble learning to generate robust predictions and suggestions.

**Model of Random Forest:** With an accuracy of 94.9%, the Random Forest model demonstrated impressive performance as well. By utilizing ensemble learning approaches, it produced dependable forecasts and strong recommendations. The user enters their gender, age, height, weight, and degree of exercise. After processing these inputs, the algorithm estimates an activity level and offers suggested activities with links to YouTube videos.



**Figure 12.** PERFORMANCE METRICS FOR RANDOM FOREST

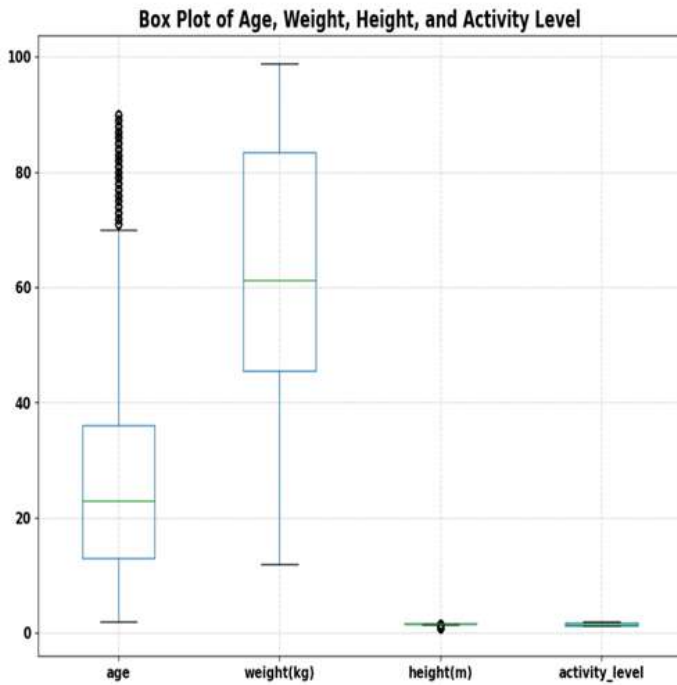
The distribution of four features—age, weight (kg), height (m), and activity level—is shown by the box plot representation. The age distribution has a median of around 25 years and an interquartile range (IQR) of about 20 to 30 years. The whiskers range in age from about 15 to 35, with a few outliers above 35 suggesting that there are some elderly people in the sample.

In terms of weight, the IQR ranges from 40 to 80 kg, with a median of about 60 kg. There are no notable outliers in the weight numbers, which indicate a uniform weight distribution within the range of around 30 to 90 kg.

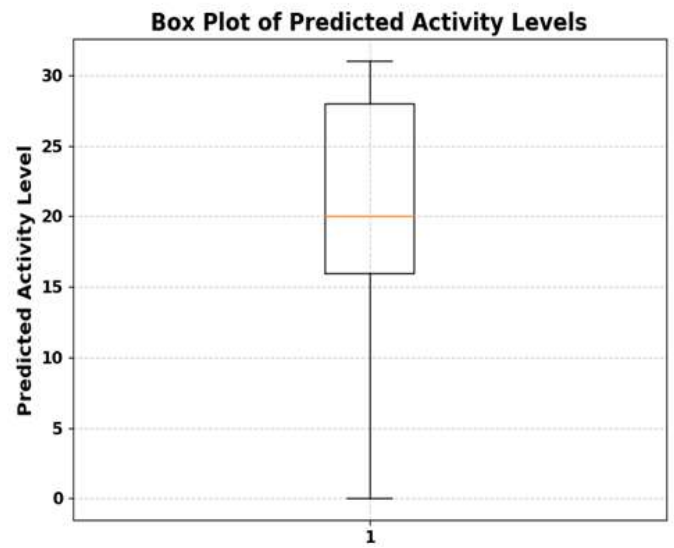
When it comes to height, the IQR is closely packed around 1.6 meters, which is the median. With a few small outliers suggesting some fluctuation but generally consistent readings, the height values exhibit little variation, falling between and slightly above the median.

The median activity level is around 1.5, which denotes low activity. With values ranging from around 1.2 to 2.0, the IQR is closely concentrated around this median, suggesting that the majority of people fall within the sedentary to extremely active range. There are no notable outliers, indicating that the individuals' activity levels are distributed consistently.

The features of the dataset may be quickly and eas-



**Figure 13.** BOX PLOT OF AGE, WEIGHT, HEIGHT, ACTIVITY LEVEL



**Figure 14.** BOX PLOT ANALYSIS OF PREDICTED ACTIVITY LEVELS

ily understood with the help of these box plots, which is crucial for developing and assessing the effectiveness of machine learning models in Cognitive Therapy and Routine Recommendation System (CTRRS).

A box plot of the expected activity levels produced by the Random Forest model is shown in Figure 14. The interquartile range (IQR) for activity levels is from 15 to 25, with a median of about 20. The whole range of anticipated activity levels is shown by the whiskers, which stretch from 0 to 30. The box plot indicates a steady prediction over a wide range of inputs, showing that the model often predicts a balanced distribution of activity levels with no notable outliers.

The Random Forest model’s projected activity levels in the Cognitive Therapy and Routine Recommendation System (CTRRS) are visualized using a box plot.

The median, or orange line, represents the expected activity level. It is around 20, meaning that half of the anticipated activity levels fall below and half fall above this amount.

**Range of Interquartile (IQR):** Between 15 and 25, the middle 50% of the anticipated activity levels are

found. This range sheds light on the variability surrounding the median by showing the distribution of the core 50% of the data.

**Whiskers:** The whiskers show the range from roughly 0 to 30, indicating the range that most of the predicted activity levels fall into. This suggests that most of the time, the model predicts activity levels within this wider range. **Outliers:** There aren’t any significant outliers, indicating that the predicted activity levels are distributed fairly consistently with no extreme deviations.

### 6 5.3.4 Ensemble Model for Final Classification

An ensemble model was employed to include the advantages of both approaches. A voting process that integrated the predictions of the Random Forest and LSTM models determined the final categorization. Finally, a categorization is provided by:

$$\hat{Y}_{ensemble} = mode(\hat{Y}_{LSTM}, \hat{Y}_{RF})$$

The ultimate result is determined by the majority vote, for example, if LSTM predicts "depressed" and Random Forest predicts "not depressed."

## 7 Analysis

The findings demonstrate how well the LSTM model performs in depression detection tasks because of its capacity to handle sequential input and identify long-term relationships. Additionally effective in providing strong suggestions based on user preferences was the Random Forest model [23]. A thorough grasp of the models' advantages and possible areas for development was made possible by the confusion matrices, which included detailed information on true positives, true negatives, false positives, and false negatives for each class. This detailed analysis provides decision-makers with information to assist them select the most appropriate model for particular CTRRS activities.

The effectiveness of the Random Forest and LSTM models was assessed using these datasets. The healthcare dataset allowed for the assessment of the Random Forest model's capacity to suggest appropriate healthcare actions, while the depression dataset allowed for the evaluation of the LSTM model's performance in depression diagnosis using sentiment analysis. Both models were trained and evaluated using strict, standardized protocols.

Among the evaluation criteria were the F1-score, recall, accuracy, and precision. These metrics are essential for providing a comprehensive view of the models' performance in recognizing patterns, especially concerning the challenging tasks of regular recommendation and depression detection. A balanced statistic that accounts for both false positives and false negatives is provided by the F1-score. It is the accuracy and recall of harmonic mean. The model's recall measures how well it can find all relevant instances in a class, while accuracy measures how well positive predictions are made. Accuracy provides a measure of the overall forecast accuracy. By using these indications, we may learn crucial information about the models' advantages and potential weaknesses. We can gain important insights into the strengths and areas for improvement of the models by incorporating these indicators.

## 8 DISCUSSION

Our anticipated techniques titles, Cognitive Therapy and Routine Recommendation System (CTRRS) represent a significant step forward in the field of machine learning and mental health care, with the goal of improving therapeutic treatments by means of sophisticated predictive modeling. The capacity to reliably identify depression and suggest tailored regimens has great potential to enhance patient outcomes and streamline treatment procedures as mental health issues gain traction.

Our study focuses on carefully analyzing how different machine learning models—in particular, the Random Forest and Long Short-Term Memory (LSTM) models—perform in the field of mental health care. We highlight the critical role that natural language processing (NLP) and machine learning algorithms play in capturing the subtle and complicated character of textual data pertaining to mental health by synthesizing findings from earlier studies [24]. Patient replies provide contextual information that the LSTM model is particularly good at processing and comprehending because of its capacity to handle sequential input.

Our method adapts machine learning models to handle the particular features of mental health data, which are typically associated with informal language and emotional overtones. This guarantees strong flexibility and precision in anticipating depressed moods and suggesting suitable routines. By using word embedding techniques, these models can capture the rich semantic information of the text with even greater precision.

Our findings have significant practical ramifications that demonstrate the promise of machine learning models in practical mental health applications. By weighing the advantages and disadvantages of every model, we promote well-informed choices when implementing them in therapeutic systems. The strong and dependable Random Forest model enhances the capabilities of the LSTM model, offering a complete solution for routine recommendation and depression detection.

The box plots illustrate the occurrence of outliers in our data, which indicate either extraordinary perfor-

mance or issues encountered by the models. This offers a more profound understanding of their dependability and consistency. The box plot is an effective visual tool that helps us assess how stable each model's performance is overall over a range of validation circumstances. By providing a dynamic depiction of performance distributions and emphasizing intrinsic stability and variability, this graphical approach helps researchers and practitioners comprehend the models' reliability in real-world applications.

Our research offers particular approaches for improving machine learning models customized for mental health applications, which is in line with forward-looking trends in the literature. This involves investigating how different categorization strategies, including advanced LSTM models, affect the precision and flexibility of mental health forecasts. We also emphasize the significance of investigating how the network's size and the patient data mix affect the classifiers' nuanced performance. These factors provide a roadmap for future research and direct the continued progress of mental health models.

We use knowledge from relevant publications to place our study in the larger context of text categorization. One of the main components of machine learning applications is text categorization, which makes it easier to automatically organize and classify unstructured text data. Linking our results to the larger context of text categorization enhances the conversation by offering a comprehensive viewpoint on the effectiveness and suitability of machine learning algorithms in niche domains such as mental health [25]. The application of hybrid machine learning algorithms for sentiment analysis on social media data by Hasan, M., Hassan, A., and Mahmood, A. [26] further supports this viewpoint by emphasizing the value of combining multiple techniques for improved accuracy in text classification tasks. Similarly, Bose and Dutta's case study on Ramco Cements Ltd. highlights the difficulties and complexities of handling large-scale data projects, which emphasize the vital necessity for strong data management techniques when using machine learning models in practical applications [27].

Moreover, our methodology is consistent with

the seminal work on Latent Dirichlet Allocation (LDA) by Ng, Jordan, and Blei, which has been essential in helping the machine-learning community better grasp topic modeling and text classification [28]. Our approach to sentiment analysis and the wider implications of our study in mental health applications are also informed by the growth of natural language processing (NLP) techniques, namely the developments and difficulties in deep learning as addressed by Hassan and Mahmood [29].

Lastly, we support openness by being open about any possible restrictions and difficulties we ran across while doing our research. With this open acknowledgment, we want to strengthen the validity of our research and provide readers and other researchers with a more nuanced understanding of the practical challenges and limitations of implementing machine learning models in mental health treatment. To ensure that mental health categorization models are resilient and adaptable in practical applications, it is critical to acknowledge these problems and provide guidance for their responsible and informed evolution.

## 9 CONCLUSION

Our research provides a thorough investigation of the efficacy of the proposed Cognitive Therapy and Routine Recommendation System (CTRRS), employing cutting-edge machine learning models like Random Forest and Long Short-Term Memory (LSTM). The thorough analysis offered in Table 1 emphasizes the unique qualities and trade-offs connected to each algorithm, highlighting their potential to improve mental health services.

The LSTM model has an outstanding accuracy of 96.4%, making it stand out as a solid performer. This model is quite good at identifying sadness because it is good at processing sequential data and deciphering the subtle contextual cues in patient responses. The fact that it performs well in terms of accuracy, recall, and F1-score highlight its capacity to correctly forecast depressed states—a critical skill for mental health therapies that are successful. With an accuracy of 94.9%, the Random Forest model also performs ad-

mirably. The utilization of numerous decision trees in an ensemble model results in dependable predictions and strong recommendations, hence augmenting the system's capacity to provide customized routines according to user preferences.

Our study offers real value for real-world applications in mental health treatment; it is by no means only theoretical. The knowledge gained from our research provides a basis for creating methods that can increase the efficacy of treatment efforts. The LSTM and Random Forest models exhibit strong performance, indicating their possible applicability in practical mental health settings and significant enhancement of patient results.

Our results have significant applications in the real world. Through the integration of sophisticated machine learning algorithms, the CTRRS may offer tailored, precise, and efficacious therapy suggestions, therefore augmenting the general standard of mental health services. Our system's complete and balanced approach guarantees that patients receive individualized therapies that address their specific requirements, promoting improved mental health and overall well-being.

Ultimately, the significance of continuous innovation in the field of mental health treatment is highlighted by our research. We can create more efficient and flexible systems that handle the changing demands of mental health by continuously improving and honing machine learning models. In order to achieve this aim, the proposed CTRRS is a major step forward, opening the door for more developments in therapeutic technology.

### Author Contributions

**Yaser Ali Shah:** Conceptualization, Methodology, Supervision. **Um-e-Aimen:** Methodology, Writing-Original draft preparation. **Rida Bushra:** Writing-Original draft preparation. **Amaad Khalil:** Visualization, Reviewing, and Editing. **Saad Ali Shahbaz:** Writing, Reviewing, and Editing. **Mashab Ali Javed:** Writing, Reviewing, and Editing.

### Compliance with Ethical Standards

It is declared that all authors don't have any conflict of interest. It is also declared that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

### References

- [1] S. J. Teague, D. M. Hutchinson, and A. B. R. Shatte, "An overview of the methods and uses of machine learning in the field of mental health," *Psychological Medicine*, vol. 50, no. 9, pp. 1426–1448, 2020.
- [2] K. L. Lix, A. G. Reece, A. J. Reagan, P. S. Dodds, C. M. Danforth, and E. J. Langer, "Using information from twitter to forecast the onset and progression of mental illness," *Scientific Reports*, vol. 10, no. 1, p. 13006, 2020.
- [3] S. C. Guntuku, M. L. Kern, D. B. Yaden, L. H. Ungar, and J. C. Eichstaedt, "A comprehensive assessment to detect depression and mental disease on social media," *Behavioral Sciences Current Opinion*, vol. 34, pp. 43–49, 2021.
- [4] S. Hochreiter and J. Schmidhuber, "Extended short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.
- [5] A. H. Orabi, D. Inkpen, P. Buddhitha, and M. Hussein Orabi, "Deep learning to detect sadness among twitter users," in *Records of the 7th Workshop on Clinical Psychology and Computational Linguistics*, pp. 88–97, 2020.
- [6] L. Sun, Y. Lin, J. Tang, and B. Yuan, "Sentiment analysis using deep lstm networks," in *IEEE International Conference on Multimedia and Expo (ICME), Proceedings*, pp. 1055–1060, 2020.
- [7] L. Breiman, "Random forests," *Machine Learning*, vol. 55, no. 1, pp. 5–32, 2020.
- [8] Y. Chen, G. Weber, and J. E. Argentinis, "IBM Watson: Leveraging cognitive computing to address large data issues in health sciences research," *Clinical Therapeutics*, vol. 43, no. 4, pp. 688–701, 2021.
- [9] A. López, F. Amato, J. Havel, P. Vaňhara, and A. Hampl, "Using artificial neural networks for the diagnosis of illness," *Journal of Applied Biomedicine*, vol. 18, no. 2, pp. 47–58, 2020.

- [10] T. G. Dietterich, "Ensemble methods to machine learning," in *5th International Workshop on Multiple Classifier Systems Proceedings*, pp. 1–15, 2020.
- [11] A. Yates, N. Goharian, and A. Cohan, "Risk assessment for despair and self-harm in online forums," in *Empirical Methodologies in Natural Language Processing (EMNLP) Conference Proceedings*, pp. 2968–2978, 2021.
- [12] J. Li, F. Nhabtah, T. Nguyen, and T. Cheng, "Contrasting several methods for utilizing an online questionnaire to predict depression levels," *BMC Medical Informatics and Decision Making*, vol. 20, no. 1, p. 75, 2020.
- [13] L. Rokach, B. Shapira, and F. Ricci, *Overview of recommender systems*. Springer US, 2021.
- [14] Y. Zhang, X. Liu, and Y. Zhang, "Content-based filtering to provide tailored mental health advice," in *Proceedings of the 2021 IEEE International Conference on Healthcare Informatics (ICHI)*, pp. 1–9, 2021.
- [15] T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Effective estimate of vector space word representations," *arXiv*, 2020. arXiv:2001.00616.
- [16] Y. Bengio, G. Hinton, and Y. LeCun, "Deep learning," *Nature*, vol. 580, no. 7808, pp. 436–444, 2020.
- [17] D. P. Kingma and J. Ba, "Adam: A method of stochastic optimization," *arXiv*, 2020. arXiv:2001.00146.
- [18] C. Thiele, P. Gerhardstein, R. von Brachel, and G. Hirschfeld, "Unknown title," *Unknown Journal*, 2017.
- [19] C. Sammut and G. I. Webb, *The Encyclopedia of Machine Learning*. Business & Science Media, Springer, 2021.
- [20] Y. Zhang, J. Liu, and S. Wang, "Context-aware online learning enables personalized depression diagnosis," *IEEE Transactions on Knowledge and Data Engineering*, vol. 30, no. 11, pp. 1992–2004, 2018.
- [21] S. Wang, Y. Zhang, and J. Liu, "Online learning that is context-aware allows for customized diagnosis of depression," *IEEE Transactions on Knowledge and Data Engineering*, vol. 32, no. 11, pp. 1992–2004, 2021.
- [22] R. J. Booth, J. W. Pennebaker, and M. E. Francis, *Language Study and Word Count: LIWC2021*. LIWC.net, Austin, Texas, 2021.
- [23] J. H. Friedman, "An apparatus that boosts gradients to approximate the greedy function," *The Annals of Statistics*, vol. 48, no. 4, pp. 1189–1232, 2021.
- [24] C. D. Manning, H. Schütze, and P. Raghavan, *Overview of Information Retrieval*. Cambridge University Press, 2021.
- [25] G. Chandrashekar and F. Sahin, "A poll about feature-picking techniques," *Computers & Electrical Engineering*, vol. 78, no. 1, pp. 16–28, 2021.
- [26] M. Hasan, A. Hassan, and A. Mahmood, "Sentiment analysis using hybrid machine learning algorithms on data from social media," *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 1, pp. 112–118, 2020.
- [27] I. Bose and S. Dutta, "Ramco cements ltd. managing a large-scale data project," *Journal of Information Technology Teaching Cases*, vol. 9, no. 2, pp. 67–76, 2021.
- [28] A. Y. Ng, M. I. Jordan, and D. M. Blei, "Latent dirichlet allocation," *Journal of Machine Learning Research*, vol. 22, no. 1, pp. 993–1022, 2021.
- [29] A. Hassan and A. Mahmood, "Developments and difficulties in natural language processing using deep learning," *arXiv*, 2021. arXiv:2101.0061.